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BIO-INSPIRED ROBOT CONTROL FOR HUMAN-ROBOT BI-MANUAL MANIPULATION

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ABSTRACT

As robots are increasingly used in human-cluttered environments, the requirement of human-likeness in their movements becomes essential. Although robots perform a wide variety of demanding tasks around the world in factories, remote sites and dangerous environments, they are still lacking the ability to coordinate with humans in simple, every-day life bi-manual tasks, e.g. removing a jar lid. This paper focuses on the introduction of bio-inspired control schemes for robot arms that coordinate with human arms in bi-manual manipulation tasks. Using data captured from human subjects performing a variety of every-day bi-manual life tasks, we propose a bio-inspired controller for a robot arm, that is able to learn human inter- and intra-arm coordination during those tasks. We embed human arm coordination in low-dimension manifolds, and build potential fields that attract the robot to human-like configurations using the probability distributions of the recorded human data. The method is tested using a simulated robot arm that is identical in structure to the human arm. A preliminary evaluation of the approach is also carried out using an anthropomorphic robot arm in bi-manual manipulation task with a human subject.

INTRODUCTION

During the last decade, there has been an increasing demand for robots that can interact, communicate and collaborate with humans. Robots have moved inside human's leaving and working environment, therefore their behavior must shift from purely robotic to human-like. Application fields ranging from service robotics (assistive devices, entertainment robots, augmentation robots) to therapeutic devices (orthotics, prosthetics, rehabilitation robots) require human-likeness in robot movements and efficient human-robot collaboration, in order to achieve seamless robot integration in the human environment. Robots have to move and act in environments designed for humans, and more importantly use tools for executing tasks designed for humans.

Robot manipulation is a well studied field that has seen remarkable developments in the last 30 years [1–4]. Moreover, dual-arm robot manipulation has been widely investigated in the last decade [5–16]. Nevertheless, it still belongs to the most demanding challenges in robotics. Most importantly, this challenge gains more interest if robots are to become useful in common household settings which are tailored for human arms and hands.

Interaction and collaboration with humans requires humanlike behavior from the robot side. Such behavior will allow the human subject to be able to understand robot's intentions, correlate characteristics (e.g. robot configuration) with task execution, and seamlessly collaborate with the robot. For this reason past research has attempted to define laws for biomimetic trajectory planning and robot inverse kinematics [17]. Approaches for mimicking the human arm movements have been proposed [18] for everyday life tasks (e.g. drawing, handwriting). There have been also efforts to generate human-like motion by imitating human arm motion as closely as possible. In [19], a method to convert the captured marker data of human arm motions to robot motion using an optimization scheme is proposed. The position and orientation of the human hand, along with the orientation of the upper arm, were imitated by a humanoid robot arm. However, this method was not able to generate human like motions, given a desired three dimensional (3D) position for the robot endeffector. Similarly, most of the previous works on biomimetic motion generation for robots are based on minimizing posture difference between the robot and the human arm, using a specific recorded data set [20]. Therefore, the robot configurations are exclusively based on the recorded data set. In this way, the method can not generate new human-like motion. The latter is a major limitation for the kinematic control of anthropomorphic robot arms and humanoids, because the range of possible configurations is limited to the ones recorded from humans.

In order to model motion principles of human arm movements, cost functions have been also used in the past [21], [22, 23]. Hidden Markov Models (HMM) have been used for modeling arm motion towards robot imitation [24–28], as well as other unsupervised learning techniques [29–31], however most of the works are based on cost functions and optimization techniques that drive the robots based on a finite recorded set, while the models are unable to generalize. Finally, a partitioning of the human-like motion generation problem has been proposed in the past [32]. The upper arm joint values are first calculated for positioning the robot elbow, and then using that, the rest of the joints are evaluated. Such an approach can not be easily applied to robots having a kinematic structure different from that of the human upper limb though.

Although some of the previous studies have investigated the human arm motion during bi-manual tasks, inter-arm coordination has not been adequately understood. From the neurophysiology point of view, there are many studies that provide evidence that bi-manual tasks are governed by coordination patterns encoded in neural level [33–37]. However, a kinematic coordination model for bi-manual tasks is still to be defined.

In this paper we focus on the inter-arm (between the two arms), as well as the intra-arm (within one arm) joint coordination during bi-manual tasks involving collaboration of the two arms. More specifically, we model this coordination for a wide variety of every-day life tasks. Then we use this model for defining bio-inspired controllers for robots collaborating with humans. Using data captured from human subjects performing a variety of every-day life tasks employing their two arms, we propose a bio-inspired controller for a robot arm. This controller is able to learn human inter- and intra-arm coordination during those tasks. We embed human arm coordination in lowdimension manifolds, and build potential fields that attract the robot to human-like configurations. The method is tested using a simulated robot arm that is identical in structure to the human arm. A preliminary evaluation of the approach is also carried out using an anthropomorphic robot arm in bi-manual manipulation task with a human subject.

EXPERIMENTAL TOOLS AND TASKS

The experimental trials for this study involved analyzing human arm motion in bi-manual tasks. To accomplish this, an active motion capture system (3D Investigator, Northern Digital Inc) was utilized to conduct all experiments. A position sensor suit was designed for individual components which were situated on the subjects: shoulder, upper arm, forearm, and a hemisphere



Figure 1. Experimental suit equipped with markers on both arms. Trial of removing cup from bottle is shown.

suit on the hand (situated over the metacarpals). The shoulder component was designed to sit on the clavicle bone and create the base reference system as shown in Fig. 1. This limited the effect of the additional 2 degrees of freedom because of the clavicle bone motion. The components had different marker clusters from one body part to the next but were symmetric from left to right arm. In total 54 markers were used and considering one arm: 3 markers on the shoulder, 8 markers on the upper arm, 6 on the forearm, and 10 on the hand (see Fig. 1).

The experimental trials initiated with a calibration phase which is analyzed below. Then, the experiments to be used for data analysis included every-day-life bimanual tasks: removing the lid off a jar, constant contact washing of an object with a sponge, tying shoelace in common knot, block stacking both parallel and perpendicular, ripping tape off roll and placing on surface, removing tape with one hand while manoeuvring with other hand, dexterously lifting and placing spherical object with two sticks, and cutting with knife and fork. These experiments covered a broad range of motion of common daily life tasks. The tasks performed attempted to maximize full arm movement and having comparable arm joint motion and contribution. Five healthy subjects participated in the experiments (4 male, 1 female, 20 ± 3 years old, 4 right-handed and 1 left-handed).

DATA PROCESSING AND ANALYSIS

In order to track the motion of the upper limbs, we choose to use the joint angles of the shoulder, elbow and wrist. For doing so, we need to compute the center of rotation of those joints (see Fig. 2). We compute the centers of rotation using markers on the rigid bodies of upper arm, forearm and palm respectively. However, there are cases where some of the markers placed on those rigid bodies are obstructed from the camera's view. To combat this issue, a marker estimation process was created. It relied on the fact that each element of the position suit created,



Figure 2. Axes of modeled degrees of freedom and centers of rotations of the two arms.

comprised of a rigid body, and the markers attached to this body would not shift with respect to each other. Therefore by capturing one or two frames from the data which had either all, or through both frames, a combination of all markers of the rigid body, we can build all the markers' inter-relationships. These relationships can be used to estimate a missing marker provided other markers from the same body are visible.

Biological Joint Centers and Calibration

The centers of rotation of the rigid bodies upper arm, forearm and palm, coincide with the biological joint centers shoulder, elbow and wrist respectively. We used a calibration experiment, which required the human subject to attempt to move all joints simultaneously while capturing the position sensor data from the suit of markers. Then using a least squares method we were able to estimate the position of the biological centers with respect to the rigid body that precedes the kinematic chain of the arm. For example, we were able to estimate the center of rotation of the forearm (i.e. the elbow joint), with respect to the upper arm rigid body. Once these points are computed, they are projected into the base frame of reference located on the humans shoulder. Having the 3-dimensional (3D) position of the wrist and elbow, as well at the 3D position and orientation of the rigid body of the palm, we are able to analytically give a unique solution to the inverse kinematic problem, and therefore compute the 7 joint angles of the upper limb [38]. The Denavit-Hartenberg (DH) parameters of the kinematic model of the arm that we used are listed in Table 1, where L_1, L_2, L_3 are the length of the upper arm, forearm and palm respectively¹.

METHODS AND PROCEDURES

The idea of cost function minimization has been prevalent in robotic control since its inception. By penalizing the controller for unwanted manipulated variable moves or controlled variable locations, the designer may shape the profile and final output. For the robotic kinematic structure in collaboration with human users, the proposed solutions must satisfy two necessary constraints: the desired end-effector position and orientation to

Table 1. Arm model D-H parameters

i	α_i	a_i	d_i	Θ_i
1	90°	0	0	q_1
2	90°	0	0	$q_2 + 90^\circ$
3	90°	0	L_1	$q_3 + 90^\circ$
4	90°	0	0	$q_4 + 180^\circ$
5	90°	0	L_2	$q_5 + 180^\circ$
6	90°	0	0	$q_6 + 90^\circ$
7	90°	L_3	0	$q_7 + 180^{\circ}$

interact, but also the mimicry of common human configuration. Only when consideration for both is implemented in the solution will the human counterpart understand both the interactive approach and intention of the robotic device. The initial constraint can be solved easily through common manipulators with sufficient degrees of freedom. The second presents the challenge of quantifying an abstraction in anthropomorphism. The method proposed here attempts to shape the common iterative inverse kinematic solution through potential minimization. From experimental observations, a data-driven probability distribution that describes inter- and intra-arm joint coordination will be defined. Then, the probability distribution will be transformed to a potential field that will drive the robot to anthropomorphic configurations for bi-manual tasks.

Dimensionality Reduction and Inference

Experimental observation of the two arms during bi-manual tasks represents challenges due to the high dimensionality of the data. In viewing the kinematic description of both arms, 14 separate joint angles should be observed, and inter-related. In order to reduce the high-dimensionality of the data, we use the Principal Component Analysis (PCA) [39]. Let

$$\mathbf{Q} = \begin{bmatrix} \mathbf{q_1} \ \mathbf{q_2} \ \dots \ \mathbf{q_{14}} \end{bmatrix} \tag{1}$$

represent the $n \times 14$ matrix for the data set for all *n* observations of the 14 joint angles. After applying the PCA, we concluded that 4 dimensions were enough to represent most of the data variability (81%). Therefore the new low-dimensional vector that represents the 14 joint angles of both arms is given by

$$\sigma_{LR} = \mathbf{W} \mathbf{Q}^{(\mathbf{i})} \tag{2}$$

where σ_{LR} is the 4-dimensional vector, *W* is the 4 × 14 matrix with columns the 4 principal eigenvectors computed through the PCA and $\mathbf{Q}^{(i)}$ a 14-dimensional vector of all joint angles at time instance *i*. Similarly, the method was applied to one single arm,

¹Offsets in θ_i are used for having the arm at rest position (pointing down) when $q_i = 0, i = 1, ..., 7$.



Figure 3. Correlation matrix across all joints of both arms. Data from one representative subject are used.



Figure 4. Probability density function, projected in a two-dimensional space defined by the two principal eigenvectors computed using the PCA for single (inter-arm) coordination.

for describing inter-arm coordination. Three eigenvectors were chosen, being able to explain 78% of original variance, and the low-dimensional representation of the single-arm joint angles σ_R is defined. For more details of the application of the PCA in motion data the reader should refer to [40].

Characterization of inter- and intra-arm coordination

The correlation among joints of the same arm, as well as across arms, is shown in the correlation matrix in Fig. 3. As it can be seen, many joints are correlated with each other, and correlations are evident across arms as well. This correlation is then represented in low-dimensional spaces as analyzed above. From this analysis we can build joint probabilities density functions that relate the low-dimensional representation of joint angles. In other words, we construct probability density functions that model the inter- and intra- arm joint angles correlations. For visual representation only, Fig. 4 shows the probability density function of intra-arm coordination across all performed tasks in one of the subjects. It must be noted that the PDF $p(\sigma_{R_1}, \sigma_{R_2})$ was

fitted using a Gaussian Mixture Model (GMM) [41,42], in order to allow further manipulation, e.g. differentiation.

Potential Fields Through Probability Analysis

Driving a robot arm to configurations that were frequently observed in the human experiments would mean that we need to command the robot arm with a set of joint angles that lie on the region of high-probability of the PDF defined above. In order to do that, we transformed the probability density function $f(\sigma)$ to a potential field $U(\sigma)$, where:

$$U(\mathbf{\sigma}) = -f(\mathbf{\sigma}) + f_{\max}(\mathbf{\sigma})$$
(3)

where $f_{\text{max}}(\sigma)$ is the global maximum of the PDF. Potential fields have been used in robotics for a variety of reasons, especially in obstacle avoidance cases [43]. Here they are used to drive the robot configurations to regions that were observed in the human experiments. The way this is done is explained in the next sections.

Robot Inverse kinematics

The main goal in controlling the robot to collaborate with the human is not only to drive the end-effector of the robot to a specific pose \mathbf{x}_d , but also impose a configuration \mathbf{q}_R that will be anthropomorphic, or in other words, obey the inter- and intra-arm coordination of the human. For this reason, we choose to make use of the robot arm redundancy and solve the inverse kinematics iteratively using the block diagram described in Fig. 5. The robot arm angular velocity vector is given by

$$\dot{\mathbf{q}}_{\mathbf{R}} = \mathbf{J}_{\mathbf{A}}^{\dagger} \mathbf{K} \mathbf{e} + \left(\mathbf{I} - \mathbf{J}_{\mathbf{A}}^{\dagger} \mathbf{J}_{\mathbf{A}}\right) \dot{\mathbf{q}}_{\mathbf{a}} + \left(\mathbf{I} - \mathbf{J}_{\mathbf{A}}^{\dagger} \mathbf{J}_{\mathbf{A}}\right) \dot{\mathbf{q}}_{\mathbf{b}}$$
(4)

where J_A is the analytic Jacobian of the robot arm, J_A^{\dagger} its pseudoinverse, **K** is a diagonal 7×7 gain matrix, $\mathbf{e} = \mathbf{x}_d - \mathbf{x}$ is the pose error between the desired pose \mathbf{x}_d and the current one \mathbf{x} . The terms $\dot{\mathbf{q}}_a$, $\dot{\mathbf{q}}_b$ will cause *internal motion* of the robot arm, i.e. joint motion that would not affect the robot end-effector pose. This is due to the fact that they are multiplied with $(\mathbf{I} - \mathbf{J}_A^{\dagger} \mathbf{J}_A)$ that will project the motion to the null space of the robot Jacobian [38]. These terms are going to be used for imposing anthropomorphic characteristics based on the inter- and intra-arm coordination modeled using the PDFs defined above. It must be noted that for simplicity we assume that the robot arm has the same kinematics with the human arm it is replacing, and that the robot arm replaces the right human arm and collaborates with the left human arm.

Both $\dot{\mathbf{q}}_{\mathbf{a}}$ and $\dot{\mathbf{q}}_{\mathbf{b}}$ terms are computed using the potential fields $U_R(\sigma_R)$ and $U_{RL}(\sigma_{RL})$ where $\sigma_R = \mathbf{W}_{\mathbf{R}}\mathbf{q}_{\mathbf{R}}$ is the low-dimensional representation of the human right arm configuration, and $\sigma_{LR} = \mathbf{W}_{\mathbf{LR}} [\mathbf{q}_{\mathbf{R}} \mathbf{q}_{\mathbf{L}}]^T$ is the low-dimensional representation of the human right and left arm configuration. The potential



Figure 5. Block diagram for iterative inverse kinematics using the pseudo-inverse Jacobian method and additional null space terms.



Figure 6. Robot motion in the null space where robot arm is reconfigured to meet anthropomorphic configurations. Representation in the low-dimensional space, using the potential field. Three cases with different initial conditions are shown.

fields are computed using eq. (3) for the PDFs describing arm coordination respectively.

In order to capture the intra-arm (right arm) and inter-arm (right and left arms) coordination characteristics of the human, the robot is controlled using (4), where the terms \dot{q}_a and \dot{q}_b are given by:

$$\dot{\mathbf{q}}_{\mathbf{a}} = -k_a \nabla U_R \left(\mathbf{\sigma}_R \right), \quad \dot{\mathbf{q}}_b = -k_b \nabla U_{RL} \left(\mathbf{\sigma}_{RL} \right) \tag{5}$$

where k_a , k_b are positive gains. Equation (5) makes use of the robot redundancy in order to drive the robot arm to configuration that not only resemble the replaced right arm ($\dot{\mathbf{q}}_a$ term), but also coordinate with the left human arm for bi-manual tasks ($\dot{\mathbf{q}}_b$ term).

RESULTS

Initially we tested whether the null space terms and the formulation of the potential fields could drive the robot arm to anthropomorphic configurations, that would coincide with local minima of the potential functions. For this reason, we started the robot from 3 different configurations, represented them in the low-dimensional space σ_R , and observed how the term $\dot{\mathbf{q}}_a$ resulted to robot motion in the null space. Fig. 6 shows the path of



Figure 7. Robot motion using the proposed method (bio-inspired controller) and the traditional pseudo-inverse Jacobian method for solving the inverse kinematics [38], compared to real motion of the replaced human arm. Root-mean-squared error (RMSE) values are reported. Task: jar lid removal.

the robot in those 3 cases, where it is shown that the robot was successfully to regions of low potential, therefore high probability based on the human experiments.

The method was tested using a simulated scenario where the robot arm was controlled to collaborate with the left arm of the human subject in a jar lid removal scenario. We compared the resulting robot motion with the motion of the right human arm, in the case the subject was using both his natural arms. Moreover, we compared the results with a traditional pseudo-inverse Jacobian method for solving the robot inverse kinematics [38]. The results are shown in Fig. 7. The proposed method outperformed the traditional inverse kinematics, as it is seen through the mean squared error of all joints angles, computed with respect to the ones of the human subject.

However, it must be noted that the goal of the proposed method is not to always drive the robot arm to specific configurations that were observed during the human motion data collection. In fact, our main goal is to create a method that would guarantee anthropomorphism in the robot arm motion, and would be able to generalize to motion not seen during the *training* phase with the human subject. Using the proposed potential field formulation, we drive the robot arm to anthropomorphic configurations, as these are characterized by the fitted PDFs. Where this method demonstrates its effectiveness is when the initial configuration of the robotic manipulator is far removed from the desired position and orientation. The traditional inverse kinematics drives each joint without consideration of any human-like behavior: joint limits, manipulability, or even anthropomorphic intent. The controller based on the proposed method would encompass all those constraints without explicit acknowledgement. This fact



Figure 8. Human collaborating with a robot arm for removing the bottle cap. Proposed (top) and traditional inverse kinematics (bottom) methods are compared.

can be made evident from Fig. 8 showing how, given the right arm configuration, both controllers converge on a perfect solution in end-effector pose. However, the traditional controller has solved it in a way as can be deemed not-anthropomorphic. In fact, the elbow joint of the robot arm used (LWR4+, KUKA) in the traditional inverse kinematics case is bent inward, which is not compatible with the human arm structure and joint limits. However, the proposed method results to a robot configuration that is human-like, which finally promotes more efficient interaction and collaboration between the robot and the human arm.

CONCLUSIONS

As robots are increasingly used in human-cluttered environments, the requirement of human-likeness in their movements becomes essential. In this paper we introduced a bio-inspired controller for a robot arm that would drive the arm to anthropomorphic configurations in bi-manual human-robot collaboration tasks. The controller not only mimics the behavior of one human arm (intra-arm coordination), but also mimics the inter-arm coordination of two collaborating human arms. The proposed method is capable of generalizing to unseen bi-manual tasks, and result to robot motion that will improve the efficiency of the interaction and collaboration between robots and humans. The method was tested using a simulated robot arm that is identical in structure to the human arm. A preliminary evaluation of the approach was also carried out using an anthropomorphic robot arm in bimanual manipulation task with a human subject.

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